Fuzzy Logic-Based Inferencing in the Presence of Input Data Uncertainty

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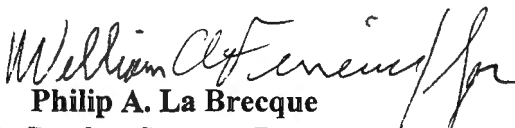
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PREFACE

Reviewed and Approved: 15 December 1997

[signature]

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REPORT DOCUMENTATION PAGE

Public reporting for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE 20 January 1998	3. REPORT TYPE AND DATES COVERED FINAL

4. TITLE AND SUBTITLE

Fuzzy Logic-Based Inferencing in the Presence of Input Data Uncertainty

5. FUNDING NUMBERS

6. AUTHOR(S)

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7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Naval Undersea Warfare Center Division
1176 Howell Street
Newport, RI 02841-1708

8. PERFORMING ORGANIZATION REPORT NUMBER

TR 10,876

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

Office of Naval Research (ONR-342)
800 North Quincy Street
Arlington, VA 22217-5000

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION/AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

In this study, the fundamental problem of handling uncertainty in the input data to a fuzzy inference system is addressed. A novel solution to this problem is derived, based on the principle of fuzzy composition. Application of this concept to the fuzzy characterization of contact speed with uncertain platform classification information is demonstrated and is shown to provide significant improvements in tracking solution quality for the single-leg target motion analysis (TMA) problem. Follow-on efforts are underway to address the issue of modeling uncertainty in the basic structure of a fuzzy inference system.

14. SUBJECT TERMS

Contact Tracking	Data Integration	Data Uncertainty
Fuzzy Logic	Fuzzy Systems	Submarine Combat Systems

15. NUMBER OF PAGES 24

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT Unclassified	18. SECURITY CLASSIFICATION OF THIS PAGE Unclassified	19. SECURITY CLASSIFICATION OF ABSTRACT Unclassified	20. LIMITATION OF ABSTRACT SAR

NSN 7540-01-280-5500

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1. INTRODUCTION

The objective of this study is to develop fuzzy logic-based inferencing methods for uncertainty management in information processing systems, with a view toward application in combat control systems (CCS). "Uncertainty management" in this context is defined as the *representation, characterization, and propagation of uncertainty* in data integration and decision support systems. In particular, this report describes the development of a new methodology for handling uncertainty in the input data to a fuzzy inference system and its application to data integration for contact management.

The term "uncertainty" is defined by Webster's Dictionary as *being in a condition of doubt.* In an information processing context, uncertainty can be thought of as *having a lack of definitive knowledge necessary to describe the process.* Uncertainty is inherent in every aspect of the data integration process, as depicted in figure 1, and encompasses a wide range of variability. Uncertainty is present in the input data to the process (such as the measurement noise in the sensors), in the algorithms designed to process the data (such as the modeling assumptions underlying the algorithms), and in the output information presented to the decision maker (such as the form and content of the human-machine interface). Efficient platform-level data integration requires effective automated management of all these sources of uncertainty and is the key issue addressed in this work.
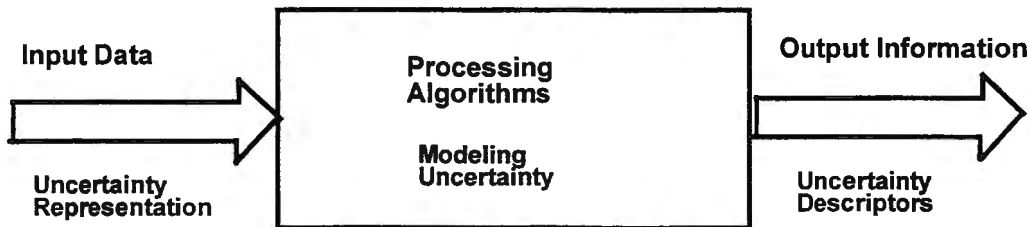
Figure 1. Sources of Uncertainty in an Information Processing System

The remainder of this report is organized in four sections. Section 2 provides the motivation for this work; in particular, it describes the naval significance and potential impact on submarine combat systems. Section 3 reviews traditional methods for handling uncertainty. Section 4 describes the technical approach for handling input data uncertainty in a fuzzy inference system. Section 5 presents experimental results for the single-leg target motion analysis (TMA) problem, including discussion of the results. Section 6 comprises conclusions and suggestions for future work.

2. MOTIVATION

Combat system information processing entails the integration of data from diverse sources for tactical picture generation and maintenance, situation assessment and planning, and resource allocation and control. As advances in sensor technology offer more possibilities in gathering related organic, off-board, and environmental data, combat system operators are faced with the challenge of integrating vast amounts of data in real time. Current methods for data integration in combat systems do not adequately account for uncertainty in an automated fashion, and these methods rely heavily on operator manipulation and human interpretation.

2.1 NAVY RELEVANCE

The evolution of submarine combat control systems (depicted in figure 2) is characterized by two main areas of advancement: (1) increased levels of automation, and (2) incorporation of advanced information processing techniques. The enabling technology underlying these advances is the revolutionary development of modern-day computer hardware and software, coupled with the Navy's movement to commercial off-the-shelf (COTS) systems.
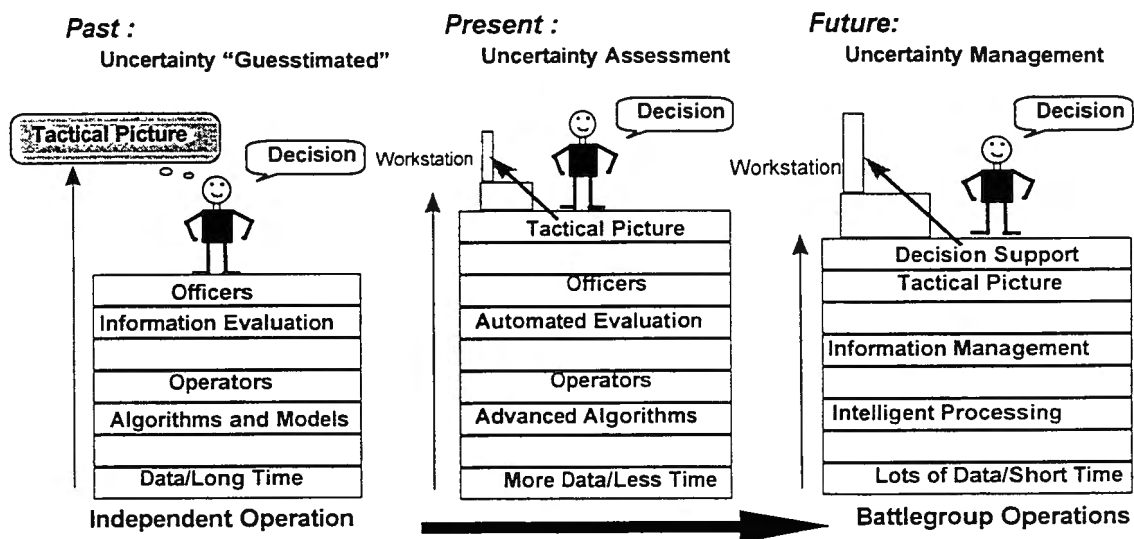

Figure 2. Evolution of Submarine Combat Control Systems

Current combat control systems, such as CCS Mk 1 and Mk 2, rely heavily on operator manipulation of input data and human interpretation of information processing results. The uncertainty inherent in the resulting tactical picture is, at best, "guesstimated" by the decision maker/commanding officer. Systems now being installed, like Target Motion Analysis Improvements (TMAI) in the Submarine Fleet Mission Program Library (SFMPL), provide a basic assessment of the uncertainty, such as the area of uncertainty (AOU) or contact-location containment ellipse. This assessment, which is possible through the use of advanced data processing algorithms and automated evaluation techniques, has been the focus of recent development efforts.

However, a rigorous method for accounting for uncertainty in deployed systems is still lacking, hence continuing the reliance on operator manipulation and human interpretation. Within this process, diverse sources provide information of variable quality. These include both acoustic and nonacoustic data streams from organic and offboard sources, environmental and kinematic descriptors, intelligence reports, and sensor characteristics. The numerous uncertainties inherent in this information, depicted schematically in figure 3, may have severe repercussions on the perceived tactical picture. The combat system of the future demands the ability to automatically manage uncertainty, that is, to provide an effective means to represent, characterize, and propagate uncertainty to support tactical decision making.
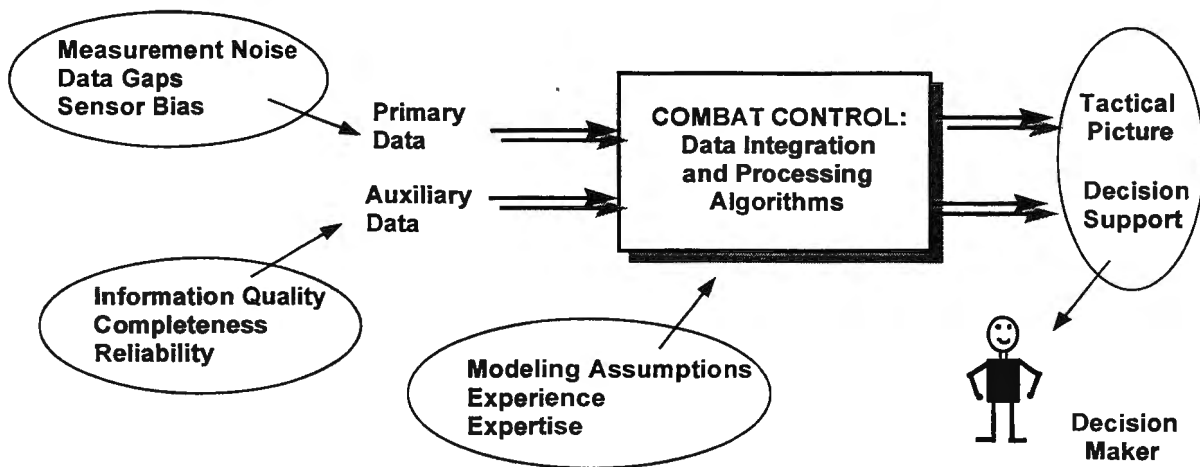

Figure 3. Uncertainty in the Combat Control Data Integration Process

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2.2 SCIENTIFIC CHALLENGE

From a scientific standpoint, the integration of heuristic information in classical control and decision theory has always been an open issue. "Heuristic information" can be defined as *subjective knowledge*, which represents linguistic data (such as rules, expertise, design guidelines) that are usually impossible to quantify using traditional mathematics. On the other hand, conventional analysis and design methods are predicated on objective knowledge; that is, they are based on the availability of a mathematical plant (or process) model to describe the behavior of the system. Heuristic information, by its very nature, is inherently uncertain and has a semantic description.[1]

Fuzzy sets are a promising alternative to traditional Boolean logic and Bayesian analysis techniques. There are now numerous industrial applications of fuzzy logic in signal processing and control systems, including subway operation (Hitachi), elevator scheduling (Mitsubishi), cruise control and automatic transmission (Nissan), and videocamera autofocus and image stabilization (Sony). The rationale underlying the relative success of fuzzy systems in engineering applications is best summarized in Zadeh's *Principle of Incompatibility*,[2] which states, "As the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which precision and significance (or relevance) become almost mutually exclusive characteristics." In particular, fuzzy logic offers a unique methodology to incorporate qualitative information described in semantic terms or via heuristics for a domain-specific problem.

3. TRADITIONAL METHODS FOR HANDLING UNCERTAINTY

In dealing with uncertainty in a large complex system, past work typically has utilized models of human reasoning and decision making. There are two broad classes of human reasoning and decision making: (1) *symbolic characterization*, which is the psychological model of what people actually do; and (2) *numerical characterization*, which is the formal mathematical model of what logicians believe a rational individual would do. These models are outlined in table 1. The former category includes the Theory of Endorsements and Reasoned Assumptions, while the latter includes the methods of Bayesian analysis, Dempster-Shafer evidential reasoning, and Zadeh's fuzzy set theory.[3] This work focuses on the numerical characterization methods.

*Table 1. Evolution of Symbolic and Numerical Models
for Dealing with Uncertainty*

Symbolic (Psychological Models)	Numerical (Mathematical Models)
Theory of Endorsements	Bayesian analysis
Reasoned Assumptions	Dempster-Shafer evidential reasoning
	Zadeh's fuzzy set theory

Conventional numerical approaches for handling uncertainty in an information processing system have focused primarily on Bayesian techniques for data characterization and analysis.[4] The Dempster-Shafer theory of evidential reasoning represents a generalization of Bayesian probability for producing inferences from uncertain information.[5,6] Recent work in the area of reasoning under uncertainty has adopted fuzzy logic as an approach that integrates heuristic domain knowledge in a numerical framework to provide "collateral or competitively better information about a physical process."[1]

A unifying framework for data integration for contact management,[7] illustrated in figure 4, was previously developed at the Naval Undersea Warfare Center (NUWC) Division, Newport, RI. This process entails (1) *data conditioning*, which associates and characterizes available data and provides uncertainty descriptors; (2) *data processing*, which processes the conditioned data to form and maintain contact tracks, propagates the uncertainties, and provides for uncertainty descriptions associated with the resulting tracks; (3) *model assessment*, which detects, interprets, and resolves anomalies arising from uncertainties in modeling assumptions; and (4) *process control*, which provides for adaptive scenario-driven processing by intelligent selection of data, models, and algorithms.
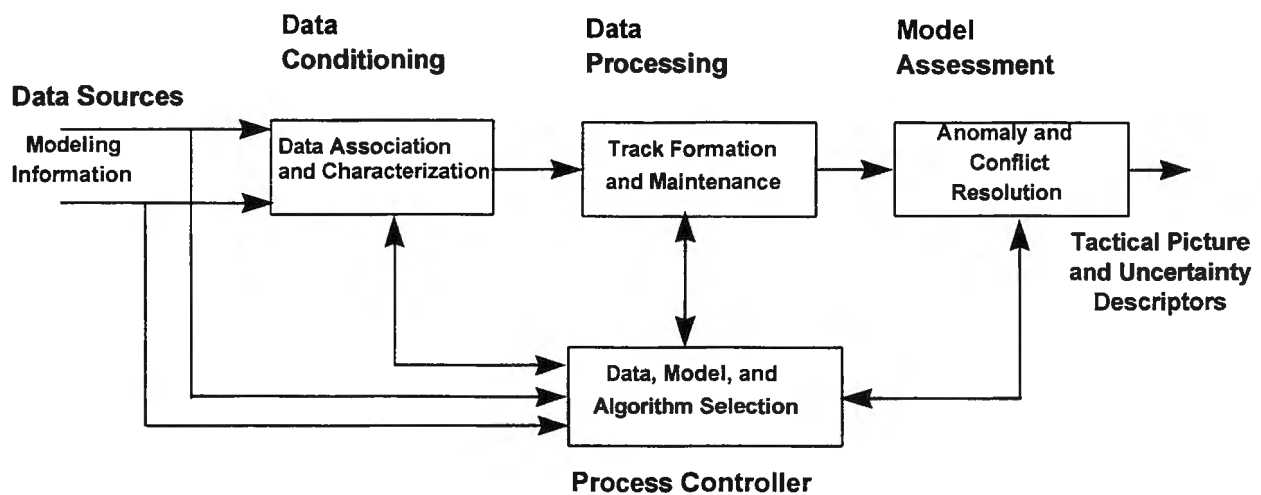
Data Sources

Data Conditioning   **Data Processing**   **Model Assessment**

Modeling Information

Data Association and Characterization → Track Formation and Maintenance → Anomaly and Conflict Resolution →

Tactical Picture and Uncertainty Descriptors

Data, Model, and Algorithm Selection

Process Controller

Figure 4. Hierarchical Model of Data Integration for Contact Management

Previous efforts at handling uncertainty in data integration have focused primarily on the data conditioning and processing stages (see figure 4). For example, in the tracking problem, the quality of the estimated track is evaluated based on *a priori* knowledge of statistical uncertainties associated with the plant model and the sensor measurements.[8] These uncertainties typically are modeled as additive, white Gaussian noise and are propagated through the conditional covariance matrix to form containment regions that indicate the final uncertainty associated with the state estimate (see Nardone et al.[9] and the references therein). Mismodeling has a severe impact on the integrity of and the uncertainties associated with the estimate. This includes erroneous assumptions, such as constant velocity, fixed propagation path, and Gaussian distributions, as well as model-order reduction as a result of linearization.

To alleviate these and other difficulties, a contact management model assessment algorithm for acoustic data processing has been investigated. Here, evidence is generated via detection of a finite set of features present in tracking residuals. Dempster-Shafer's theory of evidential reasoning has been used for combination and interpretation of this evidence; however, the results can be inconclusive if there is a high degree of conflict in the evidence.[10] To overcome this limitation, the application of fuzzy logic to model assessment was investigated,[11,12] leading to the development of techniques as described in this report for handling uncertainty in the input data to a fuzzy inference system. Uncertainty management in data integration remains an outstanding technical issue and constitutes a significant Navy problem and scientific challenge.

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4. TECHNICAL APPROACH

This effort addresses the question of handling uncertainty in the *input* data to a fuzzy inference system (FIS), that is, the issue of characterizing and propagating an inexact input. A novel solution to this problem has been derived based on Zadeh's Compositional Rule of Inference[13] and is discussed in subsection 4.2. Follow-on efforts are in progress to address the question of *modeling* uncertainty in the basic structure of an FIS (figure 5). Future studies are proposed to investigate the theoretical relationships between Bayesian probability and fuzzy systems theory (which is based on *possibility*).

4.1 PROBLEM SETUP

From a mathematical perspective, an FIS is a nonlinear functional mapping from a vector of crisp inputs $\underline{x}$ to a crisp output $\hat{y}$; $f\underline{x} \rightarrow \hat{y}$. As depicted in figure 5, an FIS consists of the following basic components.

1. *Fuzzifier:* converts crisp input numbers to membership values in fuzzy input membership functions. These membership functions provide a qualitative description of the input variables in semantic terms, such as *low*, *medium*, or *high*. The membership values are denoted as fuzzy input memberships in figure 5.

2. *Inference engine:* maps the fuzzy input memberships to a single fuzzy output set based on applicable rules from the knowledge base. This fuzzy output set is the result of aggregating all the output membership functions from the rules that are triggered by the given inputs.
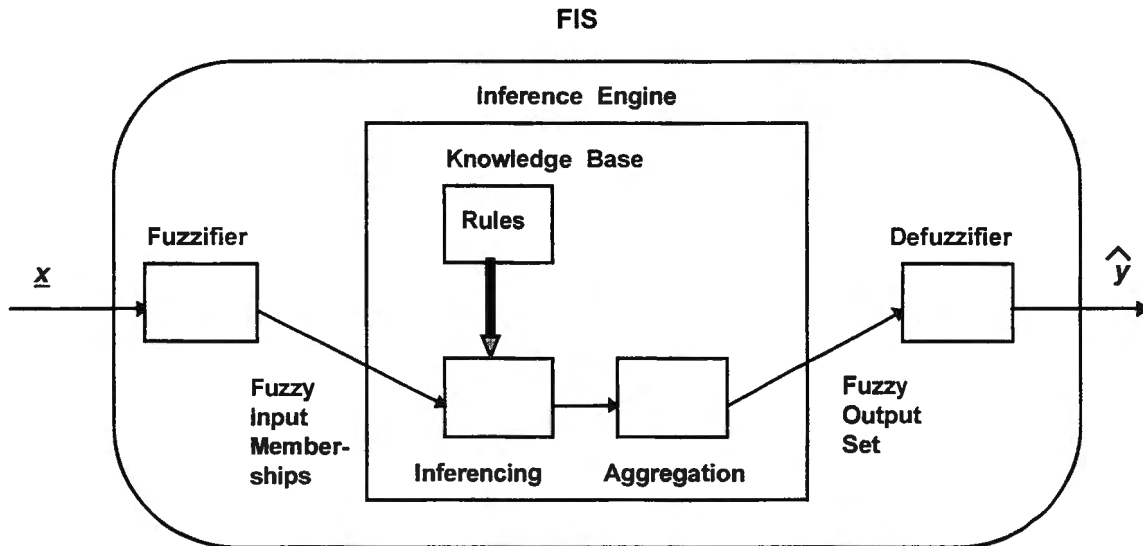

Figure 5. Basic Structure of a Fuzzy Inference System (FIS)

3. *Defuzzifier:* converts the fuzzy output set to a crisp output value for subsequent usage, such as the controller output in a feedback system. This crisp output is representative of the fuzzy output set, analogous to the expected value in a probability distribution.

For simplicity and ease of discussion, only the scalar input case will be considered; that is, $\underline{x} = x$. Over the space of all possible input values, an FIS can then be considered simply as a scalar function $\hat{y} = f(x)$, as shown in figure 6. This is a prototypical engineering viewpoint of an FIS and represents a model that commonly is found in the fuzzy systems literature.[14] The power and appeal of this model stems from the use of heuristic knowledge in the form of linguistic rules, which constitute the core element of an FIS. This model has been very successfully employed in several applications, most notably in the area of control systems.[15] At NUWC Division Newport, for example, fuzzy logic has been successfully applied and demonstrated for the control of underwater weapons.[16]
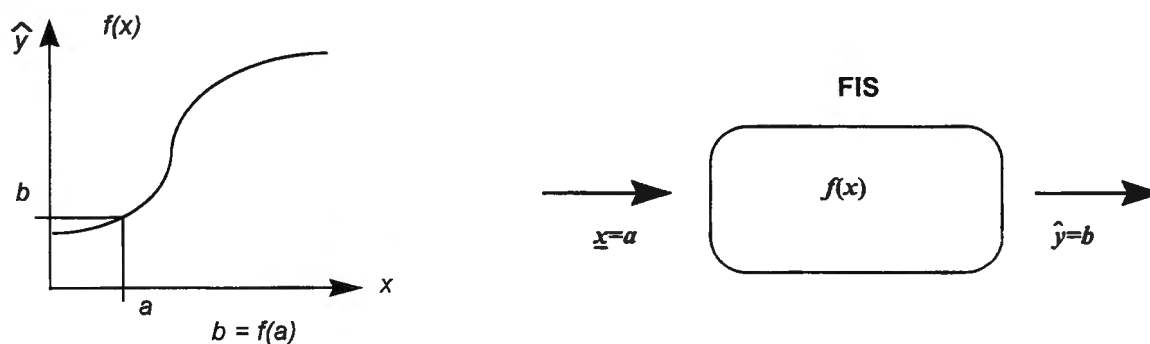

Figure 6. FIS Viewed as a Crisp Nonlinear Functional Mapping

4.2 HANDLING INPUT DATA UNCERTAINTY IN AN FIS

In this subsection, a solution is presented to the basic problem of handling uncertainty in the input data to an FIS, that is, the issue of characterizing and propagating an input that is represented with variation about $x = a$. This solution is motivated by the observation that the fuzzy output set that is produced by the inference engine of an FIS (see figure 5) constitutes a fuzzy representation of the output. In other words, the output of the inference engine is *not* a discrete, crisp quantity; but rather it is a continuous, fuzzy membership function that takes different membership values over the output variable space. This fuzzy membership function constitutes an imprecise description of the output; thus, it inherently provides a characterization of the uncertainty associated with the output. This insight, which has emerged only recently in the fuzzy literature, is the basis for further exploration into uncertainty representation and characterization in fuzzy systems.[17]
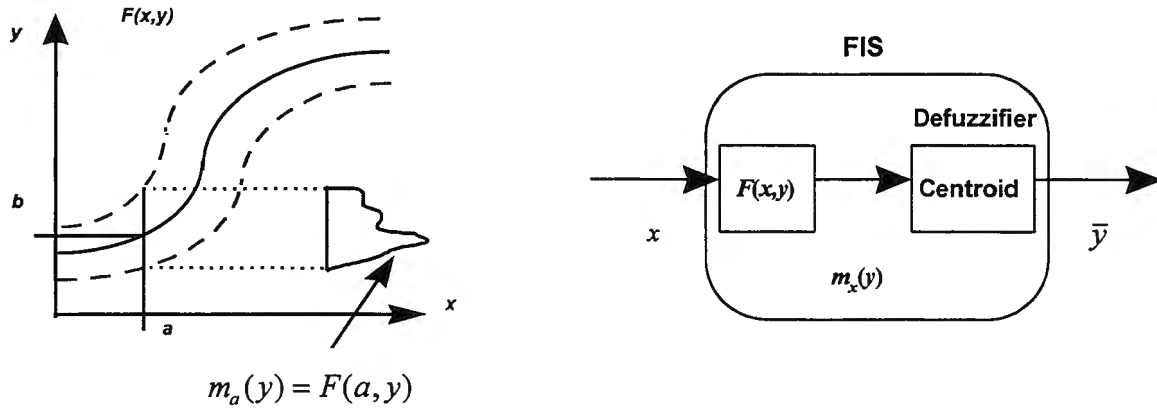
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$$m_a(y) = F(a, y)$$

Figure 7. FIS Viewed as a Fuzzy Nonlinear Functional Mapping

The interpretation of the output from an FIS inference engine as described above is shown in figure 7. For the crisp input $x=a$, the inference engine output is the membership function $m_a(y)$ that is obtained *prior* to the defuzzifier in the FIS. This concept generalizes over all possible values of x in the input space X; for every input $x \in X$, the inference engine output is a membership function $m_x(y)$. The FIS (with the defuzzifier removed) thus defines a fuzzy, nonlinear functional mapping $F(x, y)$ from a crisp input x to a fuzzy output $m_x(y)$ defined over all possible values of y in the output space Y; $F{:}x \to m_x(y)$. The defuzzifier provides a crisp output value $\hat{y}$ that is representative of the fuzzy output set $m_x(y)$; for instance, centroid defuzzification is defined by

$$\bar{y} = \frac{\int m_x(y) \cdot y \cdot dy}{\int m_x(y) \cdot dy}.$$

This interpretation of the FIS inference engine output can be regarded as the "fuzzy analog" of the statistical representation of a random variable by means of its probability distribution. It should be noted that the fundamental mathematical axioms that govern the fuzzy representation are very different from the axioms of probability; for instance, the area under the fuzzy membership function does not integrate to 1 as is required for a probability distribution. Hence the properties of the representations, as well as their interpretations, are quite distinct.

Variation in the crisp input value has a natural representation in the form of fuzzy input data membership; that is, input data uncertainty about $x=a$ can be characterized by the fuzzy membership function $\mu_a(x)$. The propagation of this fuzzy input data through the FIS involves the *composition* of the fuzzy membership function $\mu_a(x)$ and the nonlinear functional mapping $F(x, y)$. The inference engine output $M_{\mu_a}(y)$ is a fuzzy output set and is given by

$$M_{\mu_a}(y) = F(x,y) \circ \mu_a(x), \tag{1}$$

where the "o" operator indicates fuzzy composition derived from the Compositional Rule of Inference for fuzzy logic.[6] This is schematically depicted in figure 8, where $\mu_a(x)$ is the fuzzy input data about $x=a$ and is propagated through the FIS mapping $F(x, y)$ to give the fuzzy output set $M_{\mu_a}(y)$. The fuzzy composition of equation (1) can be expressed as

$$M_{\mu_a}(y) = \underset{\forall x}{S}\left[T\big(F(x,y), \mu_C(x,y)\big)\right], \tag{2}$$

where the T-norm and S-norm operator pair indicates the fuzzy AND and OR operations, and $\mu_C(x,y)$ is the cylindrical extension of input data membership $\mu_a(x)$ to the x-y plane; that is, $\mu_C(x,y) = \mu_a(x) \; \forall \, y$.
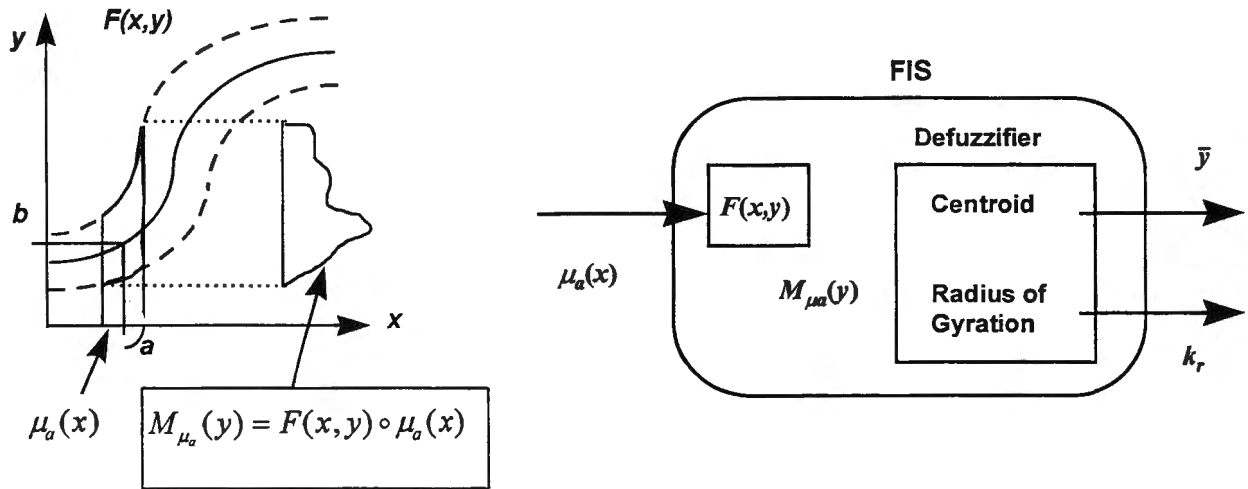

Figure 8. Propagation of Fuzzy Input Data Through the FIS Mapping to a Fuzzy Output Set

A common situation in fuzzy logic is where the logical AND and OR operators are implemented by the *min* and *max* functions, respectively. In this instance, the fuzzy composition of equation (1) reduces to

$$M_{\mu_a}(y) = \max_{\forall x}\left[\min\left(F(x,y), \mu_C(x,y)\right)\right].$$ (3)

The defuzzifier output is expanded to give (1) $\bar{y}$, the centroid of the fuzzy set $M_{\mu_a}(y)$; and (2) k_r, the radius of gyration about the centroid $\bar{y}$. Like the centroid, the radius of gyration is a concept borrowed from mechanics and represents a measure of the variability of the fuzzy set about the centroid in terms of second moments. It is defined as

$$k_r^2 = \frac{\int M_{\mu_a}(y).(y-\bar{y})^2.dy}{\int M_{\mu_a}(y).dy}.$$

This two-parameter representation of the output membership provides k_r as the measure of uncertainty about $\bar{y}$, and it can be used in subsequent processing stages to propagate the FIS output uncertainty through the data integration system.

5. RESULTS

This section presents discussion of an example FIS for describing the speed of an underwater acoustic contact based on available classification information. This is a two-rule single-input/single-output system that provides a fuzzy characterization of contact speed with only the platform classification (see figure 9). It should be noted that this is a simplified version of a speed FIS that describes contact kinematics based on classification and normalized blade-rate[18] and is used to demonstrate the application of fuzzy systems methods to data integration for target motion analysis (TMA).

5.1 INEXACT INPUTS

The speed FIS depicted in figure 9 is employed to illustrate the methods discussed previously for the propagation of uncertain inputs through a fuzzy system. The input *classification* ranges from 0 to 1, with *classification*=0.0 having membership 1 in class *diesel,* and *classification*=1.0 having membership 1 in class *nuclear*. The membership functions for the input classes *diesel* and *nuclear* are displayed in the fuzzifier. The output *speed* ranges from 0 to 40 knots, with membership functions for output classes *low* and *high* as shown in the inferencing block of the inference engine. These speed membership descriptions assume that the blade-rate is known to be "medium." The rules, which have equal weighting, are (1) IF classification is diesel, THEN speed is low, and (2) IF classification is nuclear, THEN speed is high.
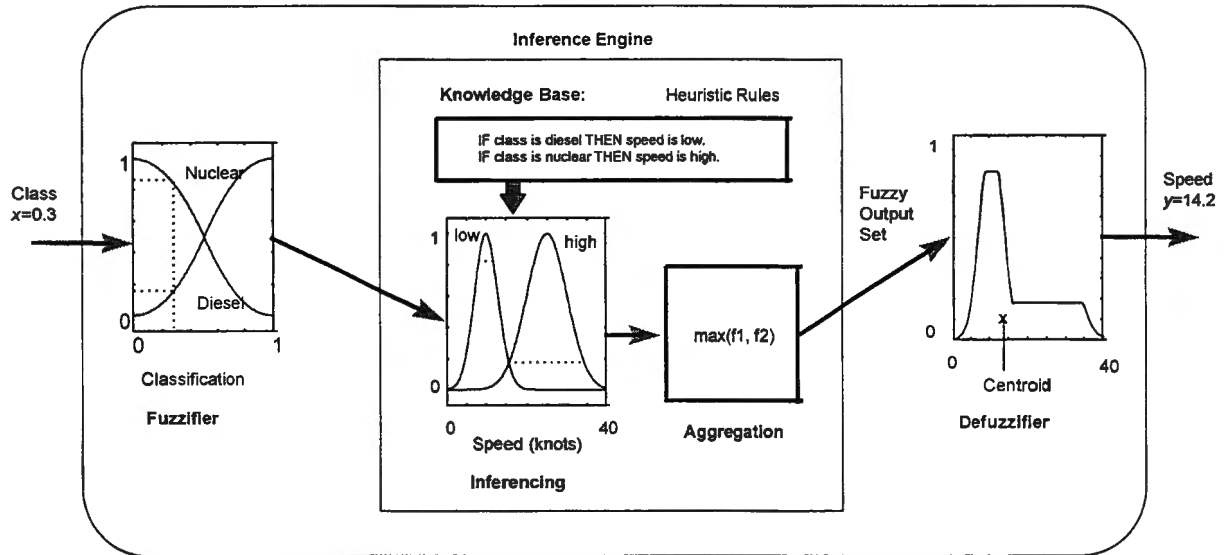

Figure 9. Speed Characterization FIS

When the input is known precisely (crisp input of *classification* = 0.3), the standard processing algorithms of fuzzy logic apply. The fuzzy output set obtained from the inference engine is plotted in the defuzzifier block of figure 9 and shows the *possibility* values associated

with contact speed in the range of 0 to 40 knots. For instance, a speed of approximately 10 knots has possibility of 0.8, and speeds in the range of 15 to 35 knots have possibility of 0.2. Two example cases of uncertain inputs and the resulting fuzzy output sets from the speed FIS are shown in figure 10 in comparison with the crisp input case. The propagation of these two inputs through the FIS by means of equation (3) is described as follows.

1. *Classification is approximately 0.3.* This input is represented by a Gaussian membership function with mean 0.3 and standard deviation 0.05 (figure 10 (a)) and is given by

$$\mu_{0.3}(x) = \exp\left[-(x - 0.3)^2 \Big/ 2 * 0.05^2\right].$$

The propagation of this input through the speed FIS is depicted in figure 11 and describes the computational mechanics of fuzzy composition. Figure 11(a) shows the cylindrical extension of $\mu_{0.3}(x)$ to the *x-y* plane; that is,

$$\mu_{0.3}(x,y) = \mu_{0.3}(x) \quad \forall y.$$

The fuzzy nonlinear functional mapping $F(x, y)$ is the composite surface formed by taking all output membership sets for the entire range of input values. This surface for the speed FIS is shown in figure 11(b). Given the fuzzy input $\mu_{0.3}(x)$, the conditioned surface $Fc(x, y)$ is the pointwise AND of this input and the fuzzy mapping $F(x, y)$. That is,

$$Fc(x,y) = \min\left(F(x,y), \mu_{0.3}(x,y)\right),$$

and it is illustrated in figure 11(c). The fuzzy composition of input $\mu_{0.3}(x)$ and mapping $F(x, y)$ is completed by projecting the conditioned surface $Fc(x, y)$ onto the output y, forming the fuzzy output set

$$M_{\mu_{0.3}}(y) = \max_{\forall x}\left[Fc(x, y)\right] = F(x, y) \circ \mu_{0.3}(x).$$

$M_{\mu_{0.3}}(y)$ represents the output response of the FIS to the uncertain input $\mu_{0.3}(x)$ and is depicted in figure 11(d). This output speed membership has an increased level of possibility of 0.3 in the 15- to 35-knot interval, thus making it more plausible for the contact to be in this speed range while maintaining a possibility of 0.8 at approximately 10 knots. Since higher speeds are now more plausible, this reflects an increased uncertainty in the contact state estimate owing to the possible variation in classification.

2. *Classification is between 0.2 and 0.4.* This input is characterized by a uniform membership function in the interval 0.2 to 0.4 (figure 10(a)). The propagation of this input through the speed FIS follows the process described above, and the resulting fuzzy output set is shown in the comparative diagram of figure 10(b). There is an attendant increase in the contact

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speed possibility, both at approximately 10 knots and in the 15- to 35-knot interval. In a TMA context, this will result in a larger number of contact tracks that have to be formed, maintained, and assessed as a result of the increased uncertainty in platform classification.

(a) Uncertain Input: Classification Membership

(b) Fuzzy Output: Speed Possibility
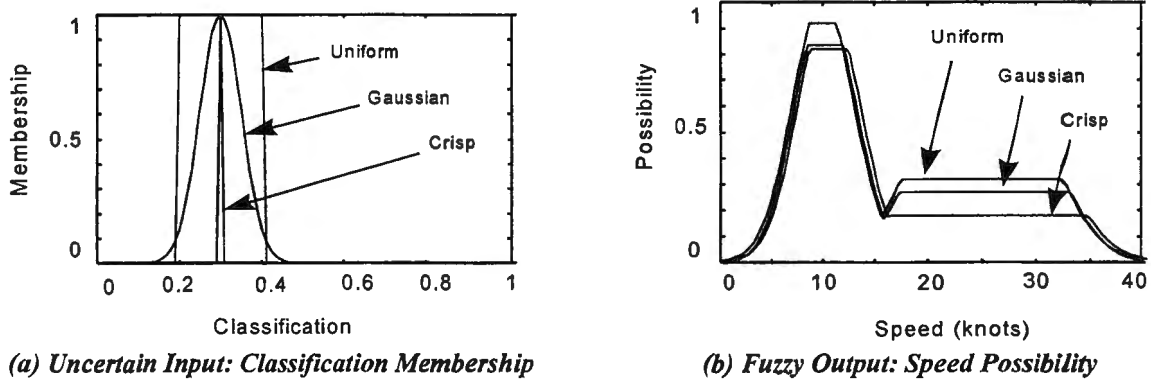
Figure 10. Uncertain Input and Fuzzy Output

(a) Input Classification: Cylindrical Extension

(b) Fuzzy Mapping: Speed FIS

(c) Conditioned Surface

(d) Fuzzy Output: Speed Characterization
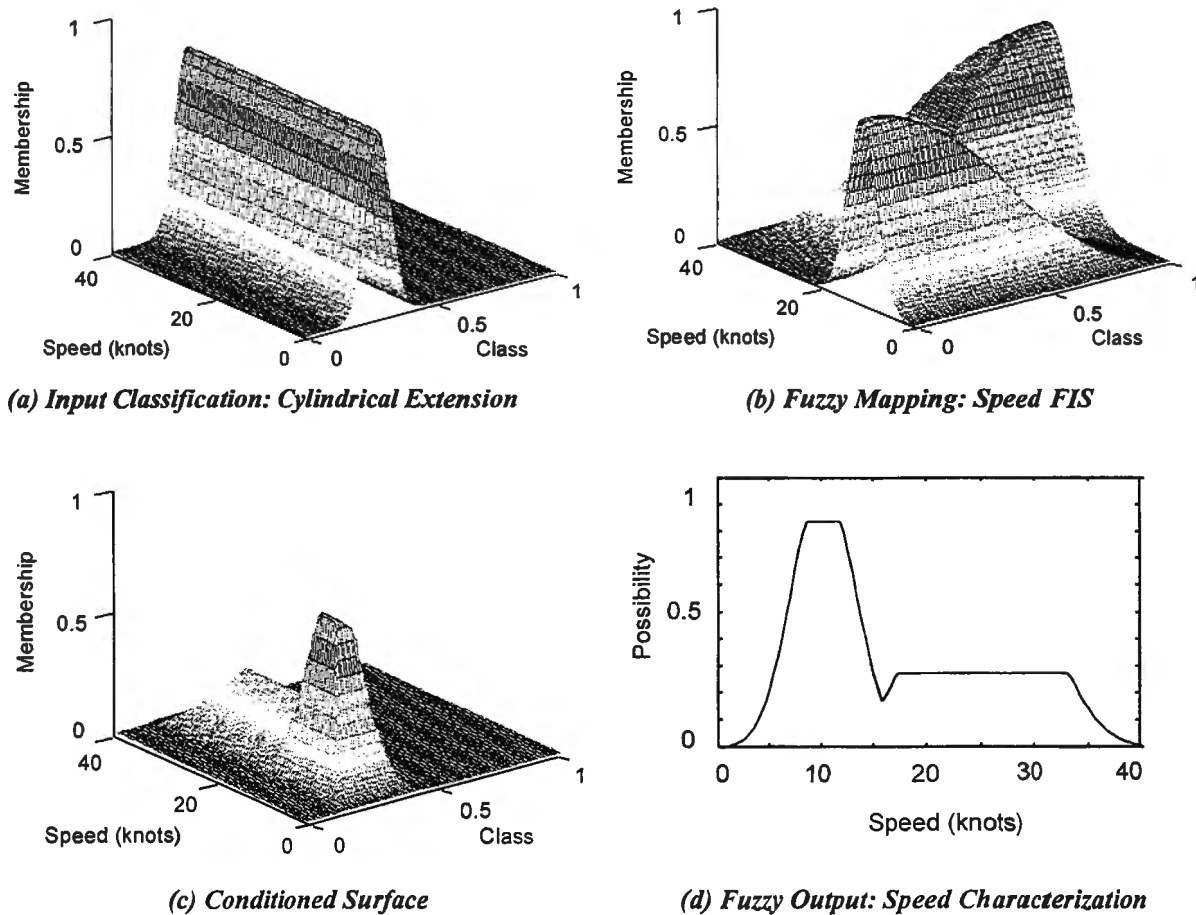
Figure 11. Fuzzy Composition: Computational Mechanics for the Gaussian Input

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5.2 APPLICATION: SINGLE-LEG TMA

This example considers the bearings-only TMA problem, which is to estimate contact location and motion parameters (state) using a time series of bearing measurements. A fundamental property of bearings-only TMA is that the contact range is not observable for a single-leg of own-ship motion (a *leg* is defined as a time interval of constant platform velocity). The range becomes observable only after an own-ship maneuver followed by a second leg of motion. This introduces a time latency in the estimation process, owing to towed array sensor instability induced by the maneuver and the necessity of collecting sufficient data on all legs of motion. This time delay may be unacceptable under certain tactical conditions when rapid estimates, albeit of poorer solution quality, are desired.

For the single-leg TMA problem, from the point of view of the range-normalized relative solution,[19] the sequence of sphere-bearing measurements is plotted in figure 12(a). The maximum likelihood estimate of the relative motion parameters (that is, bearing $\hat{\beta}$, bearing rate $\hat{\dot{\beta}}$, bearing acceleration $\hat{\ddot{\beta}}$) results from a least-squares curve fit, as shown. The three-parameter end-point solution

$$\left[\hat{\beta}_i \; \hat{\beta}_f \; \left(R_f \Big/ R_i \right) \right],$$

where subscripts i and f indicate initial and final time and R denotes range, allows us to parameterize all constant-velocity contact tracks in a range-dependent fashion. These possible tracks constitute an infinite continuum of tracking solutions that optimally fit the measurements. A discrete set of the tracks within the minimum and maximum initial range constraints of 2 kyd and 20 kyd is illustrated in figure 12(b). It should be noted that all these tracks are equally likely, so the final range of the contact is indeterminate within the derived range-constraint boundaries.
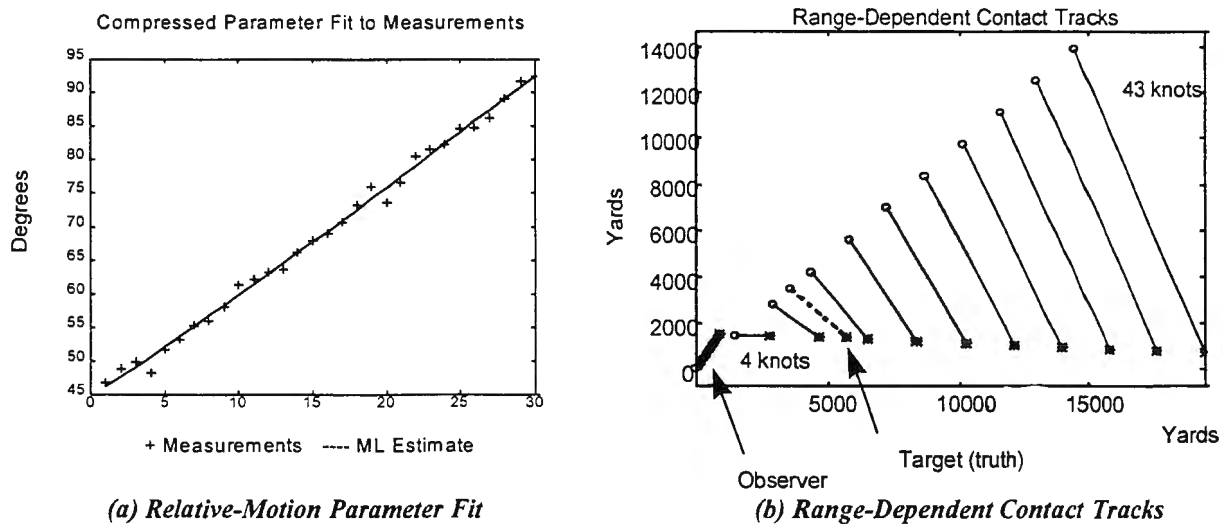

(a) Relative-Motion Parameter Fit

(b) Range-Dependent Contact Tracks

Figure 12. Relative-Motion Parameter Fit vs Range-Dependent Contact Tracks

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For this scenario, the classification input is $\mu_{0.3}(x)$, indicating the platform is more likely to be a slow-moving diesel than a relatively fast-moving nuclear (with some associated uncertainty). The resulting fuzzy characterization of contact speed is depicted in figure 11(d). This kinematic information is integrated with the single-leg TMA family of solutions to provide fuzzy weights associated with the different contact tracks. The weighted tracks are schematically illustrated in figure 13, where the intensity of the track is directly proportional to its weighting. It can be seen that the track region around the 10-knot speed constraint has the greatest weight, resulting in the final range to target having maximum possibility in the 3- to 6-kyd range. In contrast to the traditional relative solution of figure 12(b), a better quality tracking solution has been obtained.
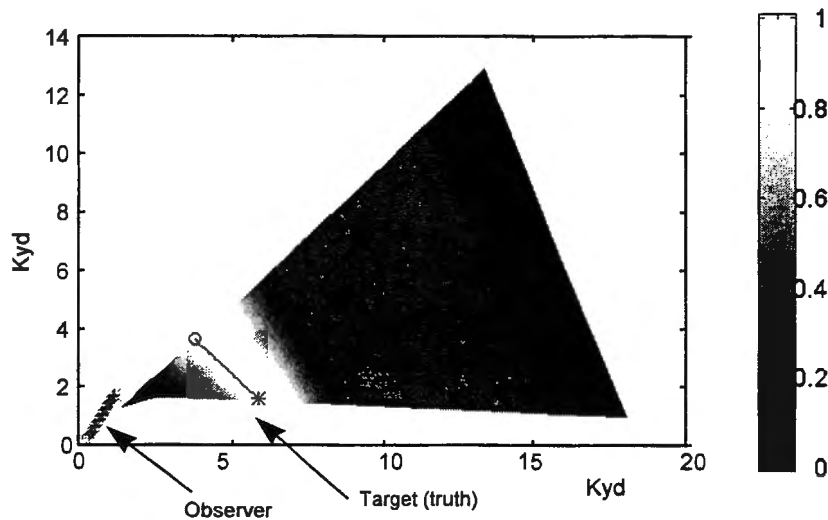

Figure 13. Contact Track Assessment: Fuzzy Weights

5.3 MISSING INPUTS

The "missing input" situation occurs when the available data are inadequate to describe one or more inputs to an FIS, that is, the available information is incomplete. This situation is handled by considering the missing input to be an input value with "infinite" uncertainty. For an FIS input, this uncertainty is modeled as a uniform membership function that spans the range of the input variable from its lower to upper limit. This approach mirrors the method used in a probabilistic context, where missing measurements are modeled by a nominal value with a very large variance.

Consider the speed FIS depicted in figure 9. If the classification of the contact is unknown, the input is described as shown in figure 14(a). The resulting speed output, which is depicted in figure 14(b), is essentially an aggregation of the two speed-class memberships of the system. Here, the assumption underlying the speed membership description is that the blade-rate is known to be "medium." There are two intervals of equivalent possibility for the contact speed, corresponding to diesel and nuclear platform classes. Integrating this information with the

single-leg TMA family of solutions (figure 12(b)) results in the contact track assessment shown in figure 15. It can be seen that the lack of classification information has resulted in a multimodal speed possibility surface and is reflected in the fuzzy weighting associated with the tracking solutions.
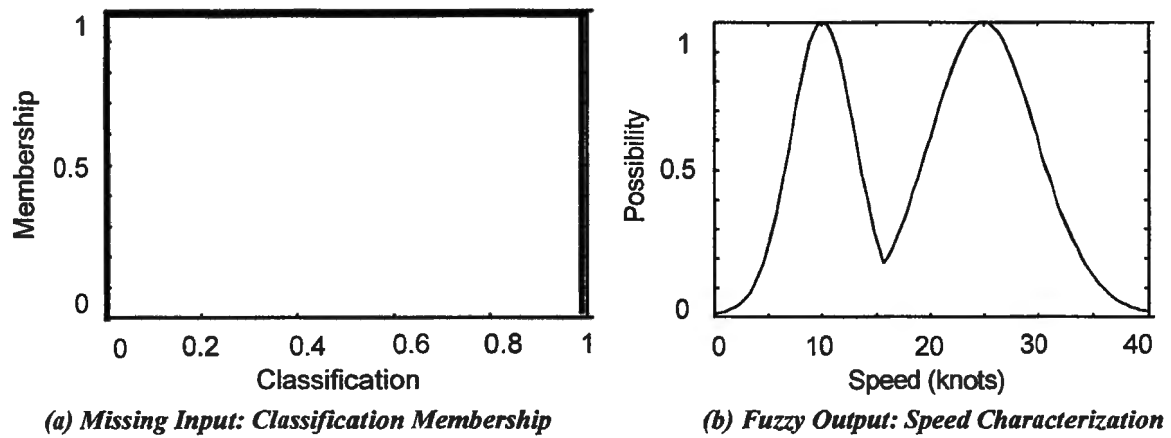

(a) Missing Input: Classification Membership   *(b) Fuzzy Output: Speed Characterization*

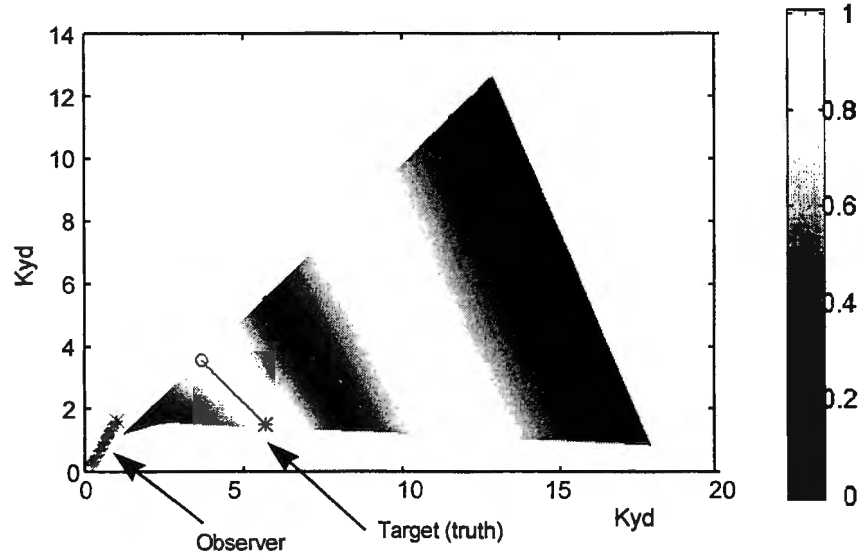*Figure 14. Missing Input and Fuzzy Output*

Figure 15. Contact Track Assessment: Fuzzy Weights

5.4 COMPUTATIONAL ISSUES

The computation of the fuzzy nonlinear mapping $F(x,y)$ can be numerically intensive and is a function of the number of inputs and the resolution of the grid employed. For instance, the two-input speed FIS mapping with grid size of 100 takes approximately 45 minutes to compute on a Pentium 100-MHz system. However, this mapping is fixed for a given fuzzy system, so it was precomputed offline and stored prior to actual use of the FIS. A vectorized approach to the fuzzy composition algorithm was devised using the MATLAB computing environment.[20] The resultant system is found to evaluate the fuzzy output in about five seconds, thus achieving significant speed-up and realistic computing times. It is worth noting that the use of MATLAB as a development testbed results in slower run times than does the use of executables in high-level programming languages, such as C, and much faster speed-ups can be expected.

6. CONCLUSIONS

Current methods for data integration and decision support in submarine combat systems do not adequately account for uncertainty in an automated fashion, hence continuing a heavy reliance on operator manipulation and human interpretation. Fuzzy logic offers an enabling technology for automated uncertainty management in the data integration process by incorporating qualitative information described in semantic terms or via heuristics in a numerical framework. It is expected that significant benefits will be derived from this technology through (1) increased automation of operator functions and (2) improved quality of information provided to support informed decision-making, resulting in reduced manning and attendant cost savings.

In this work, a novel solution is presented to the fundamental problem of handling uncertainty in the input data to a fuzzy inference system. Application of this concept to the fuzzy characterization of contact speed with uncertain platform classification is demonstrated and is shown to provide significant improvements in tracking solution quality for the single-leg TMA problem. Follow-on efforts are in progress to address the issue of modeling uncertainty in the basic structure of a fuzzy inference system, and future studies propose to investigate the theoretical relationships between Bayesian probability and fuzzy systems theory.

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